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Research Paper

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ABSTRACT

The focus of the study was to determine the factors that influence the acceptance and use of online feedback in an undergraduate module using the modified unified theory of acceptance and use of technology (UTAUT2). The participants were third-year pre-service teachers in the Bachelor of Education degree who were taking a fully online Teaching Studies module, in addition to their specialist subject areas at one of the universities in South Africa. A survey instrument was developed from the original UTAUT2 instrument and modified where appropriate, to fit the formative feedback context. Exploratory factor analysis was used to validate the instrument. The validated instrument yielded respectable reliability and construct validity. Confirmatory factor analysis verified the measurement model. The findings suggest that hedonic motivation, perceived relevance, habit, and social influence significantly affect the behavioral intention to use and accept online formative feedback, accounting for 63.6% of the variance explained, hence, signifying their importance.

Keywords

Formative feedback, online learning, UTAUT2, hedonic motivation, behavioral intention, pre-service teachers

INTRODUCTION

The growth of online courses in higher education including massive open online courses (MOOCs) has taken the world by storm (Daniel, 2012; Muñoz et al., 2016; Suen, 2014). However, existing reports indicate that success rates in MOOC courses have been appalling, with success rates less than 7% on average (see Clow, 2013; Floratos et al., 2015; Khalil & Ebner, 2014; Suen, 2014). Most recently, low success rates have also been witnessed in traditional universities that have started offering online degree courses or on-campus online courses (Moore & Greenland, 2017). For example, attrition rates exceeding 20% have been observed across Australian open-access online degree units (Greenland & Moore, 2014).

Suen (2014) attributed the poor success for MOOCs and online degree courses or on-campus online courses to a lack of formative assessment feedback. Formative assessments or "assessment for learning" are assessments that are used to evaluate students' activities where the evidence from these activities is then used to modify teaching and learning to meet the students' needs (Baleni, 2015). A lecturer, peer or self, can provide this formative assessment feedback (Hattie, 2009; Johnson, et al., 2015). Several authors (Black, et al., 2014) posited that formative assessment feedback improves the quality of learning. Besides improving the quality of learning, formative assessment feedback is widely recognized as one of the most powerful influences on student learning (Hattie, 2009, 2013; Hattie et al., 2016; Hattie & Yates, 2013; Jonsson, 2013; Mulliner & Tucker, 2017; Shute, 2008; Zimbardi et al., 2014). However, Jonsson (2013) reported that although feedback has learning potential, students do not always make use of this potential. For instance, large classes in MOOCs and online degree courses or on-campus online courses resulted in lecturers/instructors providing generic feedback directed at all participants rather than individuals. Sometimes no feedback is offered, thereby depriving students of much valued personal feedback (Bates, 2014; Carless, 2006; Suen, 2014). However, some authors (Gallien & Oomen-Early, 2008; Leibold & Schwarz, 2015 in Dyer, et al., 2018) contend that students who received personalized feedback were more satisfied and performed academically better than those who got collective or generic feedback.

In this study, feedback was provided to pre-service teachers. Pre-service teachers are student teachers enrolled in an educational programme in a higher education institution, studying to become practicing teachers or professional teachers on certification. In this context, the pre-service teachers were in their third year in the Bachelor of Education degree. Ropohl and Rönnebeck (2019) argued that the provision of formative feedback practices to pre-service teachers would result in huge gains in student achievement once the student teachers become professional teachers on certification. Thomas, (2015) reported that by participating in feedback practices, "pre-service teachers' abilities, confidence, and beliefs about giving feedback," improved" (p.18). In addition, formative feedback practices contribute significantly to a pre-service teacher's professional competence (Ropohl & Rönnebeck, 2019).

In a recent study on pre-service teachers' understanding of learning design in MOOCs, participants found the generic type of feedback directed to all participants to be frustrating (Goto, et al, 2015). Further, since 2005 the National Student Survey (NSS) in the UK has reported that students are more dissatisfied with their assessment feedback than with other facets of their university education experience. Several authors (Leibold & Schwarz, 2015; Mulliner &Tucker, 2017; Pitt & Norton, 2017; Price et al., 2011) concur with this observation. Nevertheless, providing less-specific, less-detailed, and less individualized feedback is a motivating factor for students to use and accept formative feedback (Jonsson, 2013). Thus, this implies that the acceptance of feedback goes beyond the feedback characteristics such as timeliness and specificity. This means that there could be other factors that drive the acceptance and use of formative assessment feedback, which are the basis of this study.

Several authors (Jonsson, 2013; Ramani et al., 2017; Winstone et al., 2017) posited that the great potential held by feedback for student learning can only be harnessed if the feedback is used by the students. Also, although the importance of feedback has been well documented (Zimbardi et al., 2017; Mulliner & Tucker, 2017; Johnson, 2013), the factors that drive formative assessment feedback are not explicit in the literature.

Frank, et al. (2018) and Sambell (2016)) have argued that for formative feedback to be effective it must be embedded in authentic activities. Authentic tasks are activities that have the following characteristics:

- provide an opportunity to examine a problem from different perspectives,

- provide an opportunity to reflect and collaborate,
- are multi-disciplinary and seamlessly integrated with assessments (formative and summative assessments),
- result in the creation of a polished product (digital artefacts),
- allow competing solutions and diversity of outcome,
- are of real-world relevance and are ill-defined (Herrington et al., 2014; Herrington & Herrington, 2006).

These authentic activities thus require higher-order thinking skills for problem-solving and require a substantial investment of time and cognitive resources for them to be completed.

Muganga, (2015) reported that countries with developing economies, especially in Africa, have educational systems that are mainly driven by instructivist traditional teacher-centered pedagogies which tend to promote learning of abstract (inert) and decontextualized knowledge. These traditional methods of teaching do not prepare students for future work. In addition, these traditional strategies do not explicitly expose students to authentic learning activities and elements of 21st-century skills such as critical thinking, collaboration and creativity. Nonetheless, in countries with developed economies, constructivist-teaching strategies are the norm in learning. Ingrained in these student-centered pedagogies are authentic learning activities which prepare students for the attainment of 21st-century skills (Villarroel et al., 2018). These students are better prepared for future work since during their learning they are exposed to learning activities that have real-world relevance.

The advantages of using authentic tasks are numerous. Several authors (Frank, et al., 2018; Fox-Turnbull, 2006; McCarthy, 2013; Kearney, 2013; Sambell, 2016; Wood et al., 2013) argue that authentic learning results in significant student engagement with learning and thus enhances academic performance. Sambell (2016) posits that authentic tasks foster student engagement with feedback, something that was deemed important in this study. Since high order skills are needed in problem-solving ill-defined, complex, inter-disciplinary, multi-perspective activities, anchored in the real world, authentic tasks provide weight to the validity of the assessment activities and processes (Gikandi et al., 2011; Fox-Turnbull, 2006). Through collaboration, meaningful interaction can take place resulting in learner support and deep learning in a community of learning through the provision of feedback (Gikandi et al., 2011; Kearney, 2013; McCarthy, 2013). In addition, authentic tasks foster motivation, self -regulation, metacognition and problem solving; aspects that are important for future employability (McCarthy, 2013; Villarroel, et al., 2018). For instance, authentic assessments use high order thinking skills such as critical thinking, communication and collaboration, which prepare students for their real world of work and are important for students to thrive in the 21st century (Villarroel, et al., 2018). However, Villarroel et al. (2018) argue that the introduction of authentic assessments could be a problem if students are not used to using them but used to a tradition of decontextualized-subject-knowledge testing (a case in point in many countries with developing economies). Other barriers to the integration of authentic assessments with online feedback provision include lack of student preparation, cost of setting up connectivity infrastructure for online feedback especially in poor developing economies and bigger class sizes which may impede instructors to provide sufficient feedback (Spell et al., 2014). Muganga (2015) reported that the lack of material and technological resources in African countries provides a barrier to the integration of authentic learning into teaching. However, other authentic activities such as reflection and problem-solving, creativity, critical thinking and the use of field trips do not require technological resources and can easily be implemented. In addition, Muganga

(2015) posited that field trips can be effectively used to teach authentic learning in cases where transport costs are not prohibitive.

This study was conceived since there is a lack of information on what factors drive the acceptance of formative feedback in authentic tasks. In addition to that, the Department of Science and Technology Education in the Faculty of Education at this South African university was transitioning its Teaching Studies module in the Bachelor of Education degree from traditional face-to-face learning into a fully online module. The students involved in this study were being trained to teach in the senior and further education and teaching (FET) phase in a variety of learning areas at grade 10 to 12 level in high school and were in their third year of study. The researchers (of whom two were lecturers) anticipated that the provision of individualized formative assessment feedback would help to mediate in the understanding of the subject content (see Hattie et al., 2016; Hattie & Yates, 2014; Hattie & Yates 2013) and thus enhance learning on the new online mode of delivery. These third-year undergraduate students (pre-service) in the education degree had previously had a traditional face-to-face (f2f) / blended mode of learning in their second year and their lecturers were not sure whether the students would cope well under the new fully online learning regime. Consequently, it was important to know the factors that had a statistically significant effect on the acceptance and use of formative feedback, for lecturers to put intervention measures in place to enhance learning and thus student academic achievement.

Therefore, the research question to guide this study is:

What factors are important in pre-service teachers' decision in an undergraduate online module to accept and use formative assessment feedback during authentic tasks?

This study aims to investigate the factors that influence pre-service teachers in an undergraduate online module to accept and use formative feedback during authentic tasks. To realize the aim of the study, the following objectives were set:

- To modify an already developed UTAUT2 questionnaire to suit the context of formative assessment feedback.
- To test the modified instrument for convergent and discriminant validity using exploratory factor analysis.
- To verify the measurement model using confirmatory factor analysis.
- To investigate how the factors that influence the behavioral intention to use formative assessment feedback were moderated by biographical and technological characteristics of the students.
- To build a predictive model on factors that influence the behavioral intention to use and accept formative feedback as determined by the regression analyses.

THEORETICAL FRAMEWORK

Venkatesh, Morris, Davis and Davis created the UTAUT model in 2003. The UTAUT model was created from eight different models. These are the theory of reasoned action (TRA), the theory of planned behavior (TPB), the technology acceptance model (TAM), the combined TAM and TPB model (C- TAM TPB), innovation diffusion theory (IDT), social cognitive theory (SCT) and the motivational model (MM) (see Williams et al., 2015; Venkatesh et al., 2012). The UTAUT2, which is an extension of the UTAUT, was created in 2012 (Venkatesh et al., 2012). The basis of the UTAUT2 theory is that performance expectancy, effort expectancy, social influence, hedonic motivation and habit influence behavioral intention to use technology in a consumer context (see Vankatesh et al., 2012). In the original

UTAUT2 model gender moderated effort expectancy, performance expectancy and social influence. Further, age moderated effort expectancy, performance expectancy, facilitating conditions and social influence (see Rivis & Sheeran, 2003).

In this study, some of the original constructs of UTAUT2 were used; effort expectancy (EE), performance expectancy (PE), social influence (SI), facilitating conditions (FC), habit (HBT), hedonic motivation (HM) and behavioral intention (BI). Price value, which is one of the constructs in the original UTAUT2 model, was not included because the researchers thought that since the university provided internet connectivity and devices to the students there was no need to include it. Furthermore, the university had open labs with computers which students could use since all the other lectures were taking place on campus. Connectivity on campus was always available. Off-campus students also had free Wi-Fi access through Wi-Fi hotspots available around the city of Johannesburg. Nonetheless, those students who lived far from hotspots could still access the Wi-Fi on campus since subjects besides Teaching Studies required compulsory attendance on campus where Wi-Fi was always available. In addition, all the students in this cohort were able to submit their work indicating that price value was not important.

The other constructs incorporated into the study were perceived relevance (PR), nature of feedback language (NofL), perceived importance (PI) and self-efficacy (SE). The inclusion of self-efficacy, perceived importance, perceived relevance and nature of feedback language was informed inductively from both a literature review and the university context. The university has opened its doors to students from marginalized communities. Due to the historical background of the country (apartheid) the majority of these students went to poor schools where English is hardly used as the language of instruction. In addition, the South African language policy is complicated and promotes the use of mother tongues before English in the first three years of educational instruction, and even beyond. The majority of the students attending this South African university come from these disadvantaged black communities, where teachers in their high school years switched to their mother tongues to provide explanations. Hence, the majority of these students are not confident in the use of English or struggle to understand English at university (Inglis et al., 2011; Koch & Burkett, 2005; Ngcobo et al., 2016; Opperman, 2020). Due to this background of the majority of the students, the researchers envisioned that the nature of the language used by tutors and lecturers when they were providing feedback probably would affect the use and acceptance of formative assessment feedback. The use of English as a second language is not peculiar to South Africa but applies to all African countries. However, in South Africa there exists high levels of racial and education inequality due to the apartheid system that was in place before independence in 1994, unlike other African countries.

Secondly, despite their disadvantaged backgrounds, the majority of the students qualified for university education through sheer resilience, positive self-efficacy and perseverance (Schütze et al., 2017; Hwang et al., 2016). Consequently, the researchers deemed self-efficacy as a possible contributor to the acceptance and use of formative feedback. In addition, several authors (Rakoczy et al., 2019; Dempsey & Kauffman, 2017) posited that there was an association between self-efficacy and formative feedback. This research seeks to verify this association. Self-efficacy was selected even though several authors (Moghavvemi, 2015; Samaradiwakara & Gunawardena, 2014; Venkatesh et al., 2003; Yuen et al., 2010) had established that self-efficacy was an indirect antecedent of behavioral intention that was captured by effort expectancy and fully mediated by effort expectancy. In addition, the effect of self-efficacy on behavioral intention has had mixed results (Moghavvemi, 2015; Yuen et al., 2010). Furthermore, previous research had shown that individuals with high self-efficacy were likely to influence behavioral intention (Moghavvemi, 2015). Consequently, there was a need to investigate the importance of self-efficacy in the acceptance and use of formative feedback.

As for the inclusion of perceived relevance and perceived importance this was inspired by factors that influenced Facebook as a learning tool as reported by Escobar-Rodríguez et al. (2014). In their study, the behavioral intention to use Facebook as a learning tool for the two variables perceived advantage (which was regarded as perceived importance in this study) and perceived relevance accounted for 72% of the explained variance. The high explained variance of 72 % meant that perceived importance and perceived relevance probably affected the acceptance and use of formative feedback. In addition, the researchers were of the view that if the formative feedback was regarded as important and relevant by the students that would influence the acceptance and use of formative feedback.

The addition of new variables to the model was envisaged to enhance the model's ability of interpretation (Jen et al., 2009). Nevertheless, Venkatesh (2000) argued that too many variables would make it difficult to manage empirical data.

CONCEPTUAL FRAMEWORK

The UTAUT2 has been used widely in a variety of contexts that include consumer contexts, the acceptance of learning management systems in education, the acceptance of phablets, mobile shopping/banking and internet banking, mobile learning, mobile health and green food purchases, meta-analytic reviews, and the use of Facebook as a learning tool. The review of literature related to the original constructs of the UTAUT2 is explained below.

Performance Expectancy

Venkatesh et al, (2003) defined performance expectancy as "the degree to which the user expects that using the system will help him or her attain gains in job performance". Several authors (El-Masri & Tarhini, 2017; Huang & Kao, 2015; Koivumäki et al., 2017; Venkatesh et al, 2003; Yang, 2013) concur that performance expectancy directly influences behavioral intention in the different contexts mentioned above. In this study, performance expectancy was defined simply as the students' belief that using formative assessment feedback would be useful in their studies. This led to the hypothesis:

H1: Performance expectancy has a positive influence on behavioral intention to use and accept formative feedback.

Venkatesh et al (2003) posited performance expectancy to be more significant for young men. Yu (2012) and Venkatesh et al (2003) posited performance expectancy moderated age and gender respectively.

Effort Expectancy

Venkatesh et al, (2003) defined effort expectancy as "the degree of ease associated with the use of the system". Mixed results on the effect of effort expectancy in different contexts were evident in the literature review. Numerous authors (Arenas Gaitán et al., 2015; El-Masri & Tarhini, 2017; Huang & Kao, 2015; Yuan, 2015) reported that effort expectancy influenced the behavioral intention to adopt phablets, e-learning, internet banking and adoption of e-learning systems respectively. On the contrary, in a study based on the UTAUT2, Yang (2013), El-Masri and Tarhini (2017), and Baptista and Oliveira (2015) reported that effort expectancy did not influence behavioral intention to adopt mobile learning, e-learning systems in the USA and mobile banking respectively. Venkatesh et al. (2012) propounded that effort expectancy decreases with experience. In the context of formative feedback, effort expectancy is the degree of ease associated with students' use of formative feedback. The hypothesis generated was:

H2: Effort expectancy has a positive influence on behavioral intention to use and accept formative feedback.

Social Influence

Venkatesh et al, (2003) defined social influence as "the degree to which an individual perceives that important others believe that he or she should use the new system". Social influence comprises both social and descriptive norms (see El-Masri & Tarhini, 2017). Social norms refer to what significant others think the person ought to do (Al-Swidi et al., 2014; Ham et al., 2015). On the other hand, descriptive norms refer to the behavior of the significant other that motivates one to perform a certain behavior (De Leeuw et al., 2015). In eastern cultures, or countries with collectivist cultures, studies have shown that social influence has an effect on behavioral intention (Ham et al, 2015; Huang & Kao, 2015; Venkatesh et al, 2012; Xu, 2014; Yang, 2013). However, countries with western cultures showed contrasting results (Yuan et al, 2015). In the formative feedback context, social influence is the degree to which a student perceives how important others believe they should use formative assessment feedback. This led to the hypothesis:

H3: Social influence has a positive influence on behavioral intention to use and accept formative feedback.

The social influence used in this study comprised descriptive and social norms unlike the social influence used in prior studies, which was based on social norms only.

Facilitating Conditions

Venkatesh et al, (2003) defined facilitating conditions as "the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system". The effect of facilitating condition on behavioral intention shows mixed results. Several authors (El-Masri & Tarhini, 2017; Huang & Kao, 2015, Venkatesh et al., 2003) reported that facilitating conditions influenced the behavioral intention to use technology and e-learning systems respectively. However, in mobile banking, this was not the case (Arenas Gaitán et al, 2015; Baptista & Oliveira, 2015). The effect of facilitating conditions has been seen to decrease with technology use (experience); as soon people know how to use the technology there is no need to maintain the initial support that was needed to learn it (Venkatesh et al., 2012). In the formative feedback context, facilitating conditions is the degree of availability of technical support and infrastructure during the use of formative assessment feedback by students. This led to the hypothesis:

H4: Facilitating conditions has a positive influence on behavioral intention to use and accept formative feedback.

Habit

Habit is the degree to which individuals perform behaviors automatically (Huang & Kao, 2015; Venkatesh et al, 2012). In some UTAUT2 studies, habit directly affects use behavior and indirectly affects behavioral intention (Arenas Gaitán et al, 2015; El-Masri & Tarhini, 2017; Huang & Kao, 2015; Venkatesh et al, 2012; Xu, 2014). However, Raman and Don (2013) and Yang, (2013) disagreed in their study on the effect of habit on acceptance of a learning management system and mobile learning. In the formative feedback context, habit is the degree to which student will use formative assessment feedback with some measure of automaticity. This led to the hypothesis:

H5: Habit has a positive influence on behavioral intention to use and accept formative feedback.

Hedonic Motivation

Huang and Kao, (2015) and Venkatesh et al. (2012) defined hedonic motivation as the intrinsic motivation that causes subjects to perform a specific behavior for the sake of enjoyment. According to Venkatesh et al. (2012) and Yang (2013), hedonic motivation is an antecedent of behavioral intention and is greater for young males than females. Likewise, other authors (El-Masri & Tarhini, 2017; Raman & Don, 2013; Xu, 2014;Yang & Forney, 2013) reported that hedonic motivation influenced behavioral intention in the adoption of mobile shopping behavior, acceptance of phablets, acceptance of a learning management system and continued use of online games. However, hedonic motivation decreases with more experience since the novelty of any innovation will decline with time. In the context of formative assessment feedback, hedonic motivation is the enjoyment that results from using formative assessment feedback. The led to the hypothesis:

H6: Hedonic motivation has a positive influence on behavioral intention to use and accept formative feedback.

Nature of Language

This refers to the degree to which the language used to communicate feedback to the students was clear and friendly. This was because some of the students struggle to understand English (see Ngcobo, et al, 2016; Opperman, 2020). In the context of formative feedback, the nature of language is the degree to which the students felt that the language provided in the formative assessment feedback was unambiguous, non-authoritative and positive. This led to the hypothesis:

H7: The nature of feedback language has a positive influence on behavioral intention to use and accept formative feedback.

Perceived Relevance

The literature review suggested that perceived relevance might influence behavioral intention (see Escobar-Rodriguez et al, 2014). In the context of formative assessment feedback, perceived relevance is the degree to which the formative feedback is specific or relevant to the formative feedback needs of the students. This led to the hypothesis:

H8: Perceived relevance has a positive influence on behavioral intention to use and accept formative feedback.

Perceived Importance

The literature review suggested that perceived importance might influence behavioral intention (see Escobar-Rodriguez et al, 2014). Perceived importance is the degree of importance of the formative assessment feedback in achieving learning goals/success. This led to the hypothesis:

H9: Perceived importance has a positive influence on behavioral intention to use and accept formative feedback.

Self-Efficacy

Several authors (Moghavvemi, 2015; Samaradiwakara & Gunawardena, 2014; Venkatesh et al, 2003) posited that self-efficacy was an indirect predictor of behavioral intention. Yu (2012) posited that self-efficacy was “captured” by either effort expectancy or facilitating conditions. Thus, a low value of self-efficacy would also result in a low value for effort expectancy or facilitating conditions since the two variables are directly related (Jen et al., 2009). Yuen et al. (2010) posited that self-efficacy decreased with accumulated experience. In the context of formative feedback, self-efficacy is the degree to which an individual is confident of his or her ability to use formative assessment feedback. This led to the hypothesis:

H10: Self-efficacy has a positive influence on behavioral intention to use and accept formative feedback.

Behavioral Intention

Behavioral intention is the motivation or conscious plan to perform a certain future behavior¸ or not (Huang & Kao, 2015; Venkatesh et al, 2003). From numerous studies in different contexts using the UTAUT2 model, behavioral intention accounted for reasonably high values of explained variance, which is the measure of the degree of explanation of the concept in question. For instance, in previous studies, the explained variance were 62.8% on continued use of online games (Xu (2014), 63% on the adoption of health and fitness apps (Yuan et al, 2015) and 72% on the factors that influenced Facebook as a learning tool (Escobar-Rodriguez, et al,2014). Consequently, based on the literature reviewed above, research hypotheses were formulated and are shown in the Figure 1 below.

Moderators

According to Venkatesh et al. (2003), moderators can either “amplify or constrain the effects” of the major determinants. Age, gender, subject specialization, place of ICT access, level of ICT proficiency, province and whether first-generation university student or not moderated the effect of the constructs on behavioral intention to use formative assessment feedback. The present study does not contain experience since it is difficult to capture levels of experience in studies that are not longitudinal. Besides, some students could have had formative assessments in their past years of education.

The hypotheses from the use of moderators are shown in Figure 1 above and are stated below.

H11: Gender positively moderates all predictors and behavioral intention to use and accept formative feedback.

H12: Age positively moderates all predictors and behavioral intention to use and accept formative feedback.

H13: Subject specialization positively moderates all predictors and behavioral intention to use and accept formative feedback.

H14: Place and frequency of ICT access positively moderates all predictors and behavioral intention to use and accept formative feedback.

H15: Level of ICT proficiency positively moderates all predictors and behavioral intention to use and accept formative feedback.

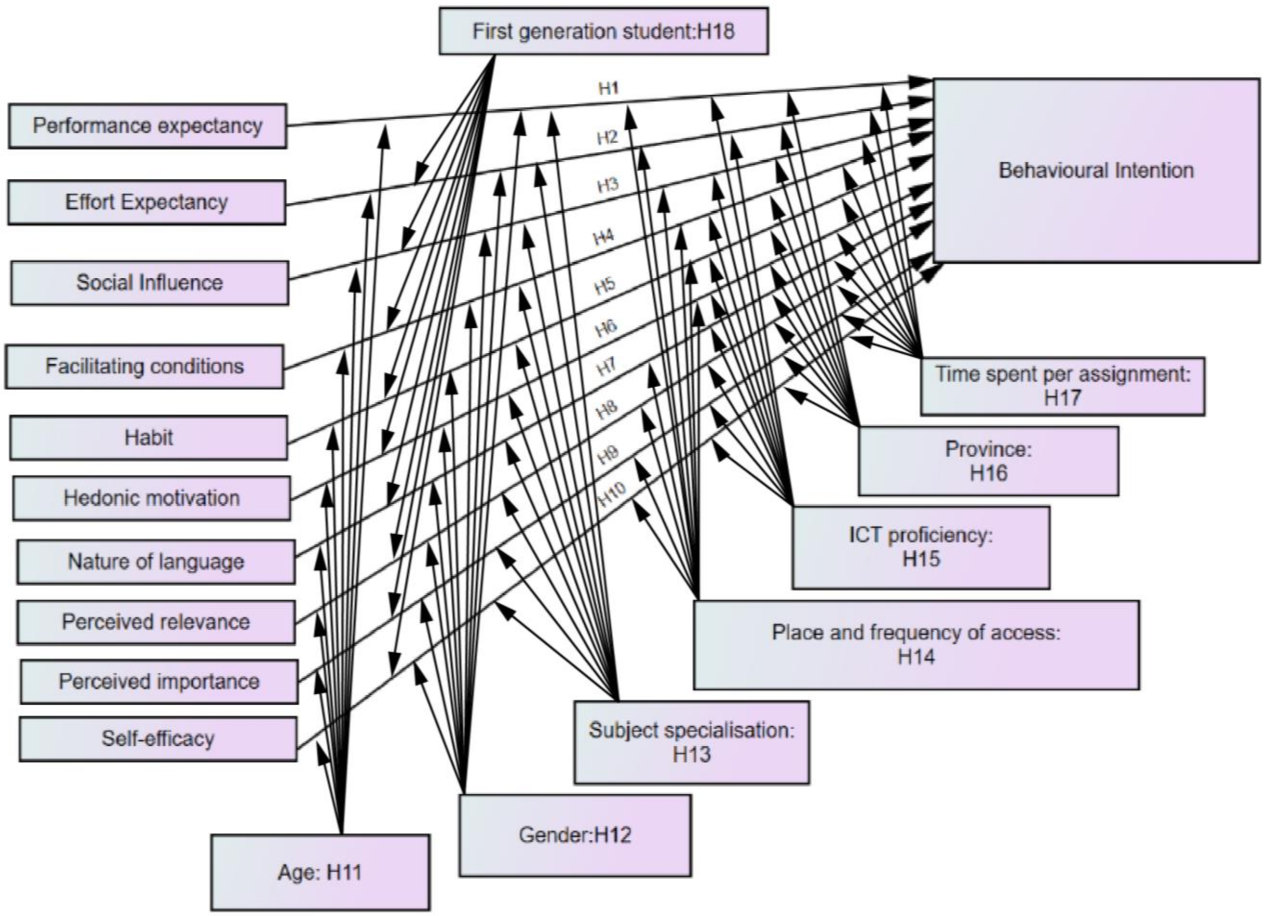
H16: Province from which the students came from positively moderates all predictors and behavioral intention to use and accept formative feedback.

H17: Being first-generation university student or not positively moderates all predictors and behavioral intention to use and accept formative feedback.

H18: The time spent per assignment doing feedback positively moderates all predictors and behavioral intention to use and accept formative feedback.

Figure 1

The Research Hypotheses



RESEARCH DESIGN

A quantitative, non-experimental correlation study was conducted.

The Instrument

The instrument used in this study was adopted from Venkatesh et al. (2012). An initial set of 39 items were developed based on 11 constructs (see Table A1 in the Appendix). The questionnaire was organized into two sections. The first section contained biographical information and the second section contained 11 constructs and 39 items. For the second section of the survey, respondents provided answers to each factor on the Likert-type agreement scale (7 points), starting from 1 (strongly disagree) to 7 (strongly agree). Likert scales are used by respondents to rate how much they agree or disagree with a statement (Sullivan & Artino Jr, 2013).

Instrument Validity

Content validity is the degree to which a measuring instrument measures what it supposed to measure (Golafshani, 2003; Heale & Twycross, 2015; Tavakol & Dennick, 2011). The researcher clearly defined the conceptual framework by doing a thorough literature review using the UTAUT2 as the theoretical lens (cf. Terwee et al., 2007).

Construct validity is the degree to which a measuring instrument measures the intended construct (Golafshani, 2003; Heale & Twycross, 2015; Tavakol & Dennick, 2011). To ensure construct validity, two experienced academics checked and reworded the original UTAUT2 questionnaire to fit the formative feedback context.

Criterion validity is the degree to which an instrument is related to other instruments that measure the same variables (Golafshani, 2003; Heale & Twycross, 2015; Tavakol & Dennick, 2011). To ensure criterion validity, the constructs in the questionnaire were adapted from Venkatesh et al. (2003) and Venkatesh et al. (2012) except for perceived relevance, perceived importance, the nature of language used and self-efficacy. In addition, the perceived relevance, perceived importance, the nature of language used, and self-efficacy questionnaire items were constructed to fit the formative assessment feedback context, again with the help of the subject experts (see Table A1).

METHODOLOGY

Settings and Participants

The study involved two cohorts of third-year students in 2017 and 2018 who were enrolled in the Teaching Studies course in the Bachelor of Education degree module fully online at one of the universities in South Africa. The students were specializing in different high school subjects that included English, Natural Sciences, Life Sciences, Life Orientation, Mathematics, Social Sciences, and Business Studies. The university has unlimited round the clock internet connectivity through Wi-Fi on campus as well as in the labs which close very late at night. The students only had the Teaching Studies module fully online but had to come to campus to attend their other subjects in person. Subsequently, both resident and non-resident students had access to the internet and could always access the fully online Teaching Studies module without any major problems. The Teaching Studies module involves the use of learning technologies in teaching and learning in the classroom and beyond. The module was driven by authentic learning activities, with the focus on the use of technology as a mediating tool rather than the technology as the object of the activity itself. Consequently, the main module outcome is to produce technologically competent teachers, effective communicators, innovative designers, interpreters, assessors and administrators, and critically reflective practitioners through technology mediation. The students engaged in these authentic tasks which included examining problems from a multi-perspective view, reflection, collaboration, problem-solving ill-defined activities of real- world relevance, creation of polished products and allowing competing solutions and diversity of outcomes (see Herrington, Reeves, Oliver & Woo, 2004; Herrington, Reeves & Oliver, 2006). The students were supported by a complement of six tutors and two lecturing staff who provided formative assessment feedback online throughout the course. At the end of the semester, the students voluntarily participated in an online survey on the use and acceptance of formative feedback.

Response Rate and Profile of the 2017 Cohort

A multi-racial 2017 cohort of 471 third year pre-service teachers in the Teaching Studies module took part in the pilot study. Of the 471 students, 214 students responded to the questionnaire giving a 45% response rate. Of the 214 students, 170 were Black, 18 were White, 10 were Indian, 8 were Colored, 2 were Asian and 6 were Other than the ones mentioned. Of the students, 137 were females and 77 males. The majority of the students were in the 22-25 age group.

DATA ANALYSIS

The individual totals for each construct were calculated for each respondent. For instance, on performance expectancy, TPE is the sum of P1, P2, P3 and P4 where P1, P2, P3 and P4 are the items under performance expectancy. Thus, summing of P1, P2, P3 and P4 to get TPE, meant that the Likert data which was ordinal data was transformed into interval data which could be used for parametric analyses such as regression and correlation. Likewise, the summing was also done for the other remaining constructs.

The data were then exported to Statistical Packages for Social Science (SPSS) version 25, where the following analyses were done:

- reliability test (Cronbach's alpha) to check for the internal validity of test items
- factor analysis to check if each of the scales were a one-factor model (unidimensional)

Further, convergent and discriminant validity were established from the scales.

Thereafter, confirmatory factor analysis was done using Amos version 26 to verify the factor structure and regression analysis was undertaken to test and build the model.

Validation of the Questionnaire

The questionnaire was validated using principal axial factoring in exploratory factor analysis (EFA). Exploratory factor analysis is important for initial scale construction (Child, 2006; Gerbing & Anderson, 1988) and hypothesis generation (Ziegler et al., 2015). Thus, exploratory factor analysis was chosen because the application of the UTAUT2 model to formative assessment is a new development (see Matsunaga, 2010). During validation, items with low factor loadings were either dropped, replaced or refined.

The improved questionnaire was then administered to a multi-racial cohort of 437 third-year Bachelor of Education degree pre-service teachers in the Teaching Studies module in 2018. Of the 437 students, 175 students responded to the questionnaire giving a 40% response rate. In terms of gender, 42.9% of pre-service teachers were male and 57.1% were female. Based on the population group, Blacks were the majority (90.9%); Whites comprised 2.9%, Indians 2.9%, Coloreds 2.3% and Others 2 % of the population. The age of participants was divided into four groups: 18–21, 22–25, 26–29 and above 30. The highest frequency occurred around the band of 22–25 age group (55.4%).

Reliability and Validity of the Questionnaire Responses

Since old items had been dropped and new items included in the instrument, exploratory factor analysis was conducted again to validate the questionnaire by simply checking for sampling adequacy and unidimensionality, which are explained in the sections below.

Sampling Adequacy Tests: The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's Test

Both the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) and Bartlett's test of sphericity measures were undertaken in this study (see Table 1 below).

Table 1

KMO and Bartlett's Test Results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.885
Bartlett's Test of Sphericity	Approx. Chi-Square	4004.111
	df	741
	p	.000

The resulting Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .885, greater than the minimum 0.5 indicating that the items had good sampling adequacy (see Kaiser, 1974). In addition, Bartlett's test of sphericity was statistically significant ($p < .05$) thus indicating the suitability of the collected data for factor analysis (Hair et al., 2006).

The KMO and Bartlett's tests of sphericity were also determined for each construct (see Table A2 in the Appendix). The KMO values of all the scales used in this study were greater than 0.5, and Bartlett's tests of sphericity was significant, thus indicating that the data was suitable for factor analysis.

Unidimensionality

All the hypothesized formative assessment feedback constructs were tested for unidimensionality, based on eigenvalues greater than one, the number of factors extracted, total variance and ratio of first and second eigenvalues. From the results, all the items loaded onto a single factor with factor loadings above 0.50 indicating good reliability, except for some items of nature of language and perceived importance.

After the one-factor model for each construct scale was established, the factor loadings for each construct scale were squared to get the communalities (see Table 2 below).

Table 2

Item Reliability of the Scales

Item	PE	EE	SI	HBT	PR	BI	NofL	PI	HM	SE	FC
1	0.58	0.754	0.628	0.499	0.437	0.726	0.560	0.086	0.423	0.419	0.664
2	0.72	0.462	0.479	0.711	0.617	0.728	0.368	0.389	0.520	0.730	0.364
3	0.69	0.503	0.621	0.567	0.582	0.763	0.29	0.487	0.449	0.245	0.343
4			0.714					0.095			
5			0.615					0.344			
6			0.427					0.510			

Note. Item numbers with blanks refer to the items that were excluded because they did not add to the unidimensionality for that construct. The items for SI represents social norms and descriptive norms

From the table above, the communalities for items, PI1, PI4, SE3 and NofL3 are less than 0.3. According to Child (2006), these communalities can be eliminated. To test the reliability of the 39-item questionnaire, Cronbach's alpha, composite reliability and average variance extracted (AVE) were used.

Cronbach's Alpha

The reliability constant alpha, which is based on average inter-item correlations, gave a reliability value of .932, which is adequate (see Brown & Moore, 2012; Tavakol & Dennick, 2011). Table 3 below shows the Cronbach's alpha value.

Table 3

Cronbach's Alpha

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	*N* of Items
.932	.938	39

The Cronbach's alpha and the corrected total item correlation for each construct were determined (see Table A3 in the Appendix). Cristobal et al. (2007) suggested a cut-off point of 0.30 for the item-total correlation. In this study, using Cristobal et al. (2007) as a yardstick, items ~NofL3, PI1, PI2, PI3 and PI5 have values less than 0.3 and all the other items have values greater than 0.3 (see Table A3 in the Appendix). Consequently, items ~NofL3 and PI1, PI2, PI3 and PI5 may be rejected/deleted.

The Validity of the Questionnaire Responses

Construct validity comprises of convergent and discriminant validity. Composite reliability and AVE are more reliable measures of validity than Cronbach's alpha (Being, 2007). Unlike Cronbach's alpha which assumes factor loadings to be the same for all items, composite reliability and AVE do not assume factor loadings to be constant which was the case in this study (Being, 2007).

Convergent Validity

Convergent validity is a measure associated with theoretically related constructs and is associated with a strong correlation coefficient, *r* greater or equal to 0.5 (Goldberg et al., 2016; Henseler et al., 2015; Strauss et al., 2016).

The conditions for convergent validity are:

- composite reliability should be above the 0.70 threshold and the AVE should be above the 0.50 threshold as recommended by Hair et al. (2006),
- or the composite reliability can be above the 0.60 threshold and AVE can be below 0.50 (Fornell & Larcker, 1981 in Huang, Wang et al., 2013).

Thus, satisfying either of the two conditions will result in convergence validity.

Evaluating Convergent Validity

An online calculator was used to calculate AVE and composite reliability (CR) (see Gouveia & Soares, 2015).

Table 4 below shows the AVE, CR and item-total correlation results.

Table 4

AVE, CR and Item-Total Correlation Results

Construct / Scale	Item-total correlation	Item-total squared	AVE	AVE[a]	CR	α
Performance Expectancy	0.605	0.366	0.6	0.775	0.8	0.929
Effort Expectancy	0.539	0.290	0.6	0.775	0.8	0.930
Social Influence	0.574	0.329	0.6	0.775	0.9	0.930
Habit	0.671	0.450	0.6	0.775	0.8	0.929
Perceived Relevance	0.627	0.394	0.5	0.707	0.8	0.929
Behavioral Intention	0.593	0.352	0.7	0.837	0.9	0.930
Nature of Language Used	0.314	0.100	0.3	0.548	0.5	0.933
Perceived Importance	0.270	0.076	0.3	0.548	0.7	0.933
Hedonic Motivation	0.597	0.357	0.5	0.707	0.7	0.930
Self-Efficacy	0.494	0.244	0.5	0.707	0.7	0.931
Facilitating Conditions	0.493	0.243	0.5	0.707	0.7	0.930

[a] denotes 0.5

Firstly, all scales, except for nature of language and perceived importance had factor loadings (inter-item correlations) greater than 0.50 thus indicating the presence of convergent validity (see Field, 2013).

Secondly, except for the nature of language, all the other constructs had CR values greater than 0.7 and AVE values greater than 0.5 thus indicating convergent validity (see Field, 2013). However, for perceived importance AVE is equal to 0.3 which is less than 0.5, but a CR value greater than 0.6, thus meeting the condition; for convergent validity the composite reliability can be above the 0.60 threshold and the extracted variance can be below 0.50 (Fornell & Larcker,1981; Huang, et al.,2013). The convergent validity is somewhat supported in this study, but one can see that the perceived importance and the nature of language have problems and may not be part of the final predictive model.

Discriminant Validity

Discriminant validity ensures that items of certain constructs are unique and that they do not correlate with other constructs' items (Goldberg, et al., 2016; Henseler, et al., 2015; Somashekhar et al., 2016; Strauss, et al., 2016).

According to Hair, et al. (2006) the condition for discriminant validity is that AVEs must be larger than their corresponding corrected item-total correlation coefficients squared, for good discriminant validity. Alternatively, the square root of the AVE for each construct must be greater than the correlation between that construct and all other constructs (see Fornell & Larcker, 1981).

Evaluating Discriminant Validity

All the constructs had AVEs larger than their corresponding corrected item-total correlation coefficients squared, thus indicating good discriminant validity (see Fornell & Larcker 1981; Hair, et al.,2006; refer to Table 4). In addition, the squared roots of the AVEs for all the constructs were greater than the correlations of a given construct and others (see Fornell & Larcker, 1981; Table 5).

Table 5

Correlation Matrix and the Square Root of the AVE for Each Key Construct

	TEE	TSI	TPR	TBI	NofL	TPI	THM	TFC	TSE	THT	TPE
TEE	**0.775**	.									
TSI	.545	**0.775**									
TPR	.433	.464	**0.707**								
TBI	.252	.279	.715	**0.837**							
TNofL	.242	.202	.386	.347	**0.548**						
TPI	.076	.162	.372	.425	.047	**0.548**					
THM	.508	.475	.530	.576	.336	.402	**0.707**				
TFC	.368	.372	.455	.474	.274	.385	.531	**0.707**			
TSE	.402	.383	.476	.457	.114	.315	.612	.459	**0.707**		
THT	.583	.564	.715	.574	.268	.302	.592	.449	.542	**0.775**	
TPE	.667	.539	.529	.366	.370	.158	.481	.402	.362	.584	**0.775**

In Table 5, the square roots of the AVEs are highlighted in bold along the diagonal. The Fornel-Larcker criterion was met since all the diagonals values were greater than the off diagonals in the corresponding rows and columns. Thus, an acceptable degree of discriminant validity was achieved.

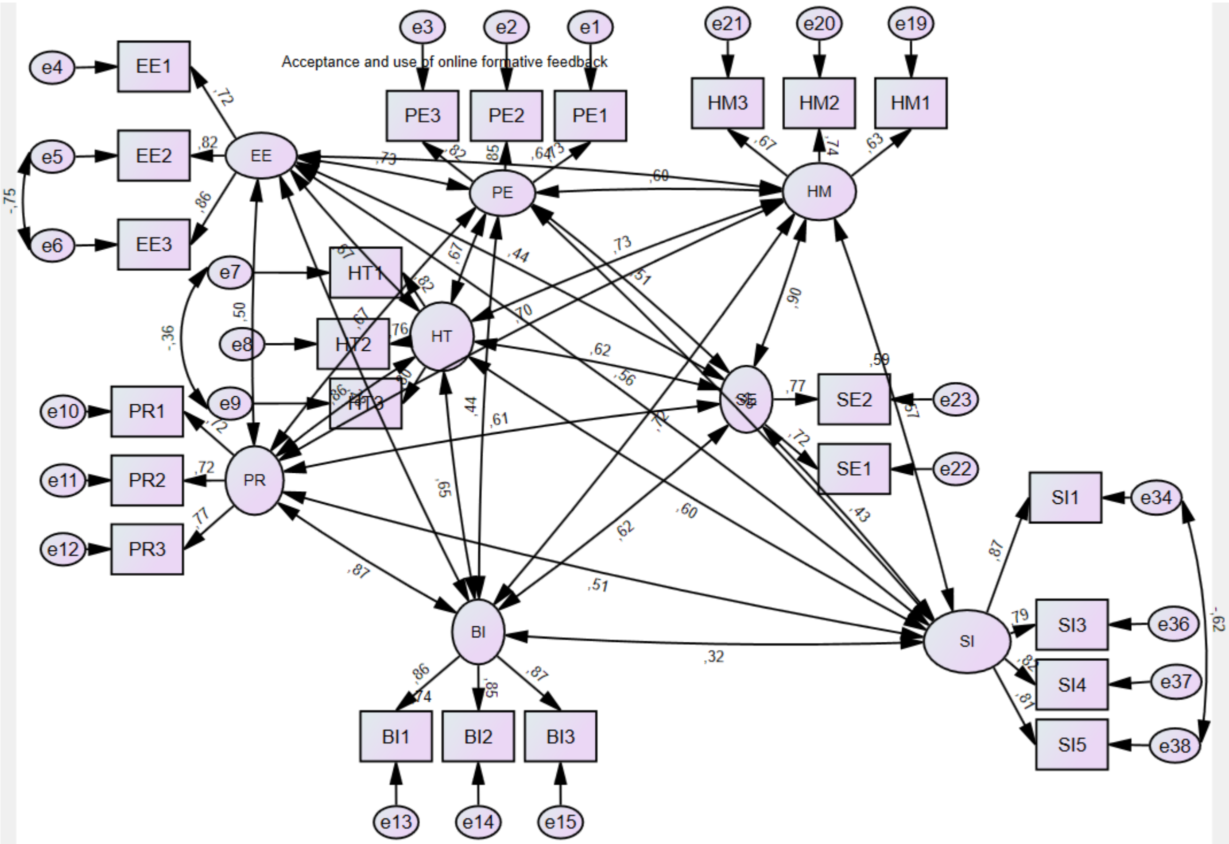
CONFIRMATORY FACTOR ANALYSIS

Confirmatory factor analysis (CFA) was used to confirm the factor structure and the fit of the measurement model to the data explored earlier on, during exploratory factor analysis. The maximum likelihood factor analysis in AMOS 26.0 was used for the analysis.

Figure 2 below shows the standardized regression weights of the observed variables (questionnaire items for instance PE1, EE1, SI2 etc.). The standard regression weights or factor loadings of the questionnaire items (observed variables) average a value of 0.7 indicating convergent validity. The correlations of the latent variables are less than 0.8 indicating divergent validity since the latent variables are not highly correlated. These two results (convergent and divergent validity) are similar to the results determined earlier on in the exploratory factor analysis above. The latent variables or unobserved variables were PE, EE, FC, SE, HM, HT, SI, NofL, PI and BI). In this analysis, the items of NofL and PI loaded very poorly just like in EFA above and were eliminated and this resulted in a better model fit. Figure 2 below shows the final confirmatory factor analysis model and the remaining latent variables.

Figure 2

The Confirmatory Factor Analysis Model



The standardized regression weights of the default model are shown in Table 6 below.

Table 6

Standardized Regression Weights

Relationship			Estimate	Relationship			Estimate
PE1	<---	PE	0.735	BI1	<---	BI	0.863
PE2	<---	PE	0.846***	BI2	<---	BI	0.848***
PE3	<---	PE	0.819***	BI3	<---	BI	0.868***
EE1	<---	EE	0.720	HM1	<---	HM	0.634
EE2	<---	EE	0.818***	HM2	<---	HM	0.738***
EE3	<---	EE	0.858***	HM3	<---	HM	0.668***
HT1	<---	HT	0.823	SE1	<---	SE	0.718
HT2	<---	HT	0.758***	SE2	<---	SE	0.771***
HT3	<---	HT	0.797***	SI1	<---	SI	0.872

Relationship			Estimate	Relationship			Estimate
PR1	<---	PR	0.717	SI3	<---	SI	0.788***
PR2	<---	PR	0.719***	SI4	<---	SI	0.817***
PR3	<---	PR	0.772***	SI5	<---	SI	0.808***

*** $p < .001$.

For each latent variable one loading was constrained to a regression weight value of 1 (this applied to all the first questionnaire items of each construct e.g. PE1, EE1, FC1) to result in an interpretable scale (Hox & Bechger, 1998). All the other factor loadings loaded at values greater than 0.7 except for two items, which loaded at 0.634 and 0.668 for HM. According to Field (2013), loadings greater than 0.7 are regarded as excellent.

Model evaluation and modification were done to improve the model fit by co-varying items from the same construct if they had a modification index greater than 10 (see Fan et al.,2016).

The resultant model fit was assessed based on the chi-square statistic, comparative fit index (CFI), the Tucker-Lewis index (TLI), root-mean-square error of approximation (RMSEA), standardized root-mean-square residual (SRMR) and *p* of close fit (PClose).

Table 7

The Model Fit Measures

Measure	Estimate	Threshhold	Interpretation
CMIN	404.376	[a]	$p = .00$
df	221	[a]	[a]
CMIN/DIF	1.830	Greater than 1 but less than 3	Excellent
CFI	0.926	>0.95	Acceptable
Tucker Lewis Index (TLI)	0.907	0.90	Acceptable
SRMR	0.061	< 0.08	Excellent
RMSEA	0.069	< 0.08	Moderate

Note. [a] denotes no value.

Table 7 above shows the cut-off points and the fitness of the model. The CFI is equal to 0.926, which is greater than 0.90 resulting in an acceptable model, although a value greater than 0.95 would have been desirable; the RMSEA is equal to 0.069, which is less than 0.08 indicating somehow a good model fit to the data (some authors suggest a cut-off point of 0.06; see Hu & Bentler, 1999). The TLI is greater than 0.90 (also a value greater than 0.95 would have been desirable, see Hu & Bentler, 1999) and the SRMR is equal to 0.0609 which is less than 0.08 indicating a good fit. The chi-square statistic (CMIN) was significant (it must be insignificant for a good fit) probably because it is sensitive to sample size, but the ratio of CMIN to degrees of freedom was equal to 1.830, which is within the required range between 1 and 3 (for cutoff criteria for fit indexes see Hu & Bentler, 1999; Schermelleh-Engel et al., 2003).

Generally, the analyzed model had a good fit as indicated by the fit indices that were used in Table 7 above. Consequently, the factor structure and the fit of the measurement model was confirmed.

In the next section, regression analyses were used to predict the relationships between predictors and the dependent variable. A regression analysis was done in SPSS rather than AMOS because it is easier to remove outliers, which influence model fit in SPSS so that the data can fit a normal distribution curve.

RESULTS

Regression Analysis

The basis of this model was to show that expectancy effort, performance expectancy, social influence, facilitating conditions, habit, perceived relevance, nature of feedback language, perceived importance, hedonic motivation, and self-efficacy influence behavioral intention, in using and accepting formative assessment feedback by third-year pre-service teachers in an online undergraduate course.

The following assumptions needed for regression to take place such as linearity between the depended variable and independent variables, constant error variance, normal distribution of the data errors (residuals) and absence of multicollinearity and corresponding tests for each assumption were undertaken. The presence of multicollinearity was tested by considering the tolerance, variation inflation factor (VIF) and condition index values. Outliers were then identified and removed since their presence affect the normality of data (see Norman, 2010). In this study, three methods were employed to identify outliers. These were the Cook's distance, Mahalanobis distance and the standard deviation.

Regression Method

At the beginning of the regression, all the independent variables TPE, TEE, TS1, THBT, TPR, TNofL, TPI, THM, TSE and TFC were entered into the regression model using SPSS enter method.

Results of the Preliminary Predictive Model

Residual Statistics

In Table 8 below, the Cook's distance is less than one (0.697) implying that there is no overly influential case that warrants exclusion from the analysis (Warren et al., 2011). However, the Mahalanobis distance is 49.954, which is greater than the critical value 18.31 at $p < .05$ for 10 variables. The value of the Mahalanobis distance that is greater than the critical value indicates there are some influential outliers in the data. The studentized residual is 3.461, which is greater than the recommended three standard deviations (Blatná, 2006). Thus, the Mahalanobis distance and the studentized residual values indicate there were some influential outliers in the data. Table 8 below shows the residual statistics of the analysis.

Table 8

Residual Statistics

Residual Statistics	Minimum	Maximum	*M*	*SD*	*N*
Predicted Value	9.43	21.55	17.95	2.200	175
Std. Predicted Value	-3.874	1.633	0.000	1.000	175
Standard Error of Predicted Value	0.214	.958	0.417	0.151	175
Adjusted Predicted Value	9.15	21.57	17.96	2.175	175

Residual Statistics	Minimum	Maximum	*M*	*SD*	*N*
Residual	-6.406	5.755	0.000	1.718	175
Std. Residual	-3.619	3.251	0.000	0.971	175
Stud. Residual	-4.304	3.461	-0.001	1.025	175
Deleted Residual	-9.058	6.520	-0.004	1.925	175
Stud. Deleted Residual	-4.555	3.583	-0.003	1.042	175
Mahal. Distance	1.558	49.954	9.943	8.763	175
Cook's Distance	0.000	0.697	0.012	0056	175
Centered Leverage Value	0.009	0.287	0.057	0.050	175

Note. TBI is the dependent variable.

The model was improved by identifying potentially influential cases (outliers) and removing them and observing for changes within the critical values in the Mahalanobis and Cook's distances, as well in the standard deviation. This was achieved by sequentially deleting cases with large residuals, that is, cases with residuals greater than three standard deviations (see Jarque & Bera, 1980) until the Mahalanobis distance was equal or less than the critical value since any Mahalanobis distances score above that critical value is a bivariate outlier.

Thirteen cases with outliers whose studentized residuals were greater than three standard deviations were removed in sequential 14 steps where in each step, two new cases were removed including the previous ones until the sample number decreased from a high of 175 to 162. In addition constructs with large significance, $p > .05$, like TPE ($p = .942$), TSE ($p = .836$), TEE ($p = .477$) and TPI ($p = .282$), TFC ($p = .159$, TNofL ($p = .715$) and TPI ($p = .282$) were also removed from the model to ensure a good fit of the model.

Results of the Final Predictive Module

Model Summary

The results of the regression indicated that the model explained 63.6% of the variance and the adjusted *R* squared value 62.7 %(the adjusted value provides a better estimate of the true population value). The *R* squared is a key goodness-of-fit measure for regression analysis. According to Pallant (2007), the total variance accounted in the model of magnitude 63.6% is respectable. Table 9 shows the model summary.

Table 9

Model Summary

Model	*R*	R^2	Adjusted R^2	*SE* of the Estimate
1	.798[a]	.636	.627	1.513

Note. TBI is the dependent variable.

[a] Predictors: (Constant), TSI, TPR, THM, THT

ANALYSIS OF VARIANCE

The analysis of variance (ANOVA) table shows the statistical significance of the model. The model is a significant predictor of behavioral intention to accept and use formative assessment feedback, $F(4, 157) = 68.610$, $p < .001$ (see Table 10 below).

Table 10

ANOVA Results

Model		Sum of Squares	*df*	Mean Square	*F*	*p*
1	Regression	628.442	4	157.111	68.610	.000 [a]
	Residual	359.515	157	2.290		
	Total	987.957	161			

Note. TBI is the dependent variable.

[a] Predictors: (Constant), TSI, TPR, THM, THT

Statistical Significance of Predictors

The larger the *t*-test and the smaller the significance, the greater the contribution of each predictor to the model. The predictors that were statistically significant were **THBT** (*p* = .001), **TPR** (*p* = .000), **THM** (*p* = .000) and **TSI** (*p* = .025) (see Table 11 below).

Table 11

Statistical Significance of Predictors

Model		Unstandardized Coefficients		Standardized Coefficients	*t*	*p*	95% CI for B		Correlations			Collinearity Statistics	
		B	*SE*	Beta			*LL*	*UL*	Zero-order	Partial	Part	**Tolerance**	VIF
1	(Constant)	2.390	1.005		2.378	0.019	0.405	4.376					
	THM	0.432	0.063	0.420	6.853	0.000	0.307	0.557	0.680	0.480	0.330	**0.617**	1.622
	TPR	0304	0.072	0.306	4.234	0.000	0.162	0.446	0.669	0.320	0.204	**0.444**	2.254
	THT	0.237	0.067	0.264	3.525	0.001	0.104	0.370	0.680	0.271	0.170	**0.412**	2.426
	TSI	-0.044	0.020	-0.124	-2.264	0.025	-0.083	-0.006	0.275	-0.178	-0.109	**0.779**	1.284

Note. TBI is the dependent variable. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Collinearity Diagnostics

In this analysis, the tolerance values are greater than 0.1 thus meeting the requirement for non-multicollinearity (see Table 11 above). In addition, values of VIF are also less than 2.5 indicating that there is no multicollinearity and the model is strong (Chen & Yao (2016). The collinearity diagnostics below indicate that there is hardly any multicollinearity in the data since all the condition indices are less than 30(see Table 12 below).

Table 12

Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	THM	TPR	THT	TSI
1	1	4.944	1.000	0.00	0.00	0.00	0.00	0.00
	2	0.028	13.377	0.03	0.01	0.02	0.02	0.98
	3	0.014	18.977	0.51	0.04	0.06	0.28	0.00
	4	0.009	23.983	0.28	0.88	0.14	0.00	0.01
	5	0.006	29.658	0.19	0.07	0.79	0.70	0.00

Note. TBI is the dependent variable.

Residual Statistics

In Table 13 below, the Cook's distance is less than one (0.155) implying that there is no excessively influential case that warrants exclusion from the analysis (Warren et al., 2011). The Mahalanobis distance is 18.555 which is close to the critical values of 18.47 at $p < .001$ for 4 predictor variables and hence an indication of no outliers which then is synonymous with Cook's distance. The studentized residual is 3.029, which is slightly greater than the recommended 3 standard deviations (Blatná, 2006). The Mahalanobis distance and the studentized residual values indicate there is hardly any influential outliers in the data.

Table 13

Residual Statistics

Residual statistics	Minimum	Maximum	*M*	*SD*	*N*
Predicted Value	12.100	21.560	18.080	1.976	162
Std. Predicted Value	-3.026	1.760	0.000	1.000	162
Standard Error of Predicted Value	0.122	0.527	0.251	0.087	162
Adjusted Predicted Value	12.210	21.590	18.080	1.974	162
Residual	-4.623	4.503	0.000	1.494	162
Std. Residual	-3.055	2.976	0.000	0.987	162
Stud. Residual	-3.171	3.029	0.000	1.009	162
Deleted Residual	-4.980	4.667	-0.001	1.560	162
Stud. Deleted Residual	-3.267	3.112	-0.001	1.019	162
Mahal. Distance	0.052	18.555	3.975	3.675	162
Cook's Distance	0.000	0.155	0.009	0.022	162

Residual statistics	Minimum	Maximum	*M*	*SD*	*N*
Centered Leverage Value	0.000	0.115	0.025	0.023	162

Note. TBI is the dependent variable.

Evaluating the Final Predictive Model

Behavioral intention to accept and use formative assessment feedback = 2.390 + 0.237*habit + 0.304*perceived relevance + 0.432*hedonic motivation - 0.044*social influence.

Hedonic motivation contributed most significantly to the model (β = 0.432, $t = 6.853$, $p < .000$). However, TPR (β = 0.304, $t = 4.234$, $p = .000$), THBT (β = 0.237, $t = 3.525$, $p = 0.001$) and TSI (β = -0.044, $t = -2.264$, $p = 0.025$) accounted for a statistically significant amount of the variance to the model but in a decreasing order of β magnitudes. In this model, social influence is inversely related to behavioral intention. The diagram below shows the pictorial representation of the model as well as the β values of the predictors and the moderators.

From the predictive model above (Figure 3), the following hypotheses were supported:

H3. Social influence has a negative influence on behavioral intention to use and accept formative feedback.

H5. Habit has a positive influence on behavioral intention to use and accept formative feedback.

H6. Hedonic motivation has a positive influence on behavioral intention to use and accept formative feedback.

H8. Perceived relevance has a positive influence on behavioral intention to use and accept formative feedback.

Though not shown in the model one can also argue that theoretically that behavioral intention influences the use and acceptance of formative feedback since behavioral intention is directly proportional to use (see Ventatesh et al, 2012).

In addition, the influence of moderators on behavioral intention to use and accept formative feedback were investigated:

H11. Gender positively moderates social influence

H12. Age positively moderates social influence

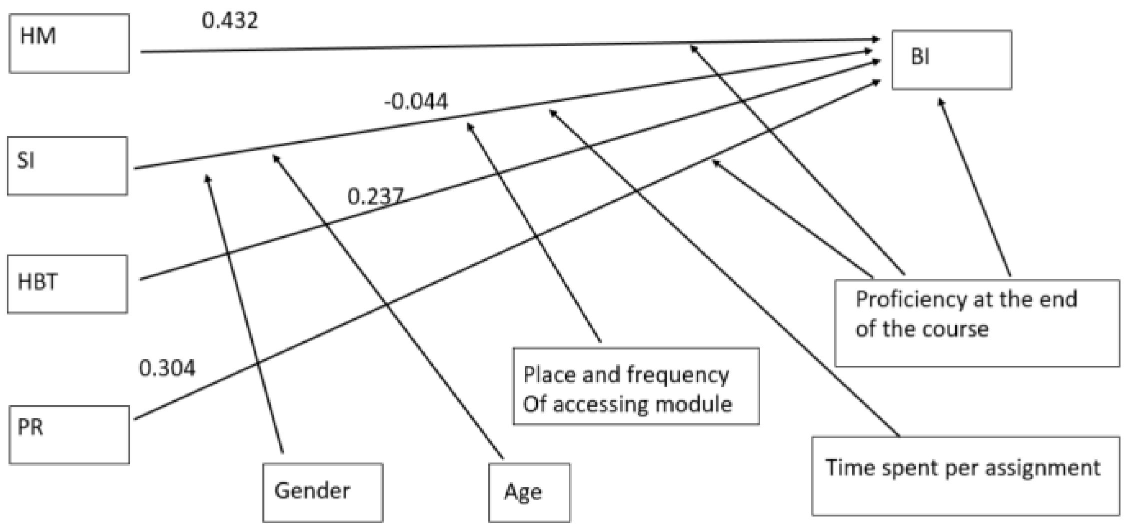
H14. Place and frequency of ICT access positively moderates social influence

H15. Level of ICT proficiency positively moderates behavioral intention to use and accept formative feedback, perceived relevance and motivation

H18. The time spent per assignment doing feedback positively moderates social influence.

Figure 3

The Final Predictive Model



DISCUSSION OF THE FINDINGS

The results of this study indicate convergences and divergences with earlier findings with the UTAUT/UTAUT2 framework, confirming unique elements of formative assessment feedback in an online environment context.

Effort Expectancy

Effort expectancy did not influence behavioral intention to use and accept formative assessment feedback. This is inconsistent with earlier findings (Venkatesh et al., 2003; Venkatesh et al., 2012). However, this result is not unexpected since with the accumulation of experience through use, the influence of effort expectancy decreases (Venkatesh et al., 2012). Probably the students had lots of experience in using formative assessment feedback in their lives or during the course.

Performance Expectancy

Performance expectancy did not influence the behavioral intention to use and accept formative assessment feedback. This is inconsistent with earlier findings (Venkatesh et al., 2003; Venkatesh et al., 2012) who posited that performance expectancy influenced behavioral intention.

Perceived Importance

Perceived Importance did not influence behavioral intention to use and accept formative assessment feedback. This result is inconsistent with Escobar-Rodrguez, et al. (2014) finding.

Self-Efficacy

Self-efficacy did not influence behavioral intention to use and accept formative assessment feedback. This result is consistent with earlier findings from several authors (Moghavvemi, 2015; Samaradiwakara & Gunawardena, 2014; Venkatesh et al., 2003;Yuen et al., 2010) who posited that self-efficacy was an indirect predictor of behavioral intention since self-efficacy was captured by effort expectancy and fully mediated by effort expectancy Thus, the insignificance of effort expectancy in this study would make self-efficacy redundant since effort expectancy did not affect behavioral intention to use formative feedback. In addition, the fact that the students had to persevere against so many odds to make it to university (through high self-efficacy) is not important as a contextual factor in the use and acceptance of formative feedback. When it comes to the acceptance and use of formative feedback one's background is not statistically significant, a finding which goes against the common narrative/discourse and is encouraging and welcome.

Nature of Language

The nature of language used in the provision of feedback did not influence behavioral intention to use and accept formative assessment feedback. This was inconsistent with literature findings where the importance of language was emphasized (see Koch & Burkett, 2005; Ngcobo, et al., 2016; Opperman, 2020). This finding is unexpected and welcome and goes a long way in convincing those people who always regard second language use as a deterrent to the acceptance of formative feedback.

Facilitating Conditions

Facilitating conditions did not influence behavioral intention to use and accept formative assessment feedback. This is inconsistent with Venkatesh et al. (2012) finding. However, according to Venkatesh et al. (2003) facilitating conditions have an influence on the behavioral intention during the early stages of technology (in this case formative assessment feedback) adoption and its effect decreases with experience/time. Thus, experienced users become less depended on external support and probably the students were in the post-adoption of formative feedback stage. In addition, all the students were accessing the fully online module on campus where connectivity was readily available and there were tutors, lecturers and support staff available to help. Therefore, this finding seems to be consistent with the support that was available in the learning context.

Habit

Habit did influence behavioral intention to use and accept formative assessment feedback. This result is consistent with earlier findings and prior research (Venkatesh et al., 2012). This probably indicates the importance of good online habits such as frequently logging online, to access and post work. The lecturers must model good behavior during module facilitation to cultivate good habits in the students.

Hedonic Motivation

Hedonic motivation had the largest effect on behavioral intention to use and accept formative feedback. This is consistent with earlier findings (Ventatesh et al., 2012). However, in this study motivation was not influenced by age nor gender. This result is inconsistent with earlier finding by Ventatesh et al. (2012). However, there was a statistically significant difference between motivation and proficiency at the end of the course, $F(3, 52.192) = 4.549$, $p = .007$. The Turkey post hoc test indicated that those who reported that their proficiency was excellent and very good, their means were statistically greater and significant than those who chose their proficiency to be fair with p values of .003 and .02 respectively. The implication is that those who were proficient were more motivated than those who were not proficient. Perhaps the blended learning mode of delivery, which took place from 1st and 2nd year meant that some students got away without acquiring information communication technology (ICT) proficiency skills and were less motivated because they were not confident in using ICT tools. With respect to motivation, there were no statistically significant difference among those students who were good, very good and excellent at proficiency. It is unfortunate that in their third year some students still felt that proficiency was not good enough (fair) and these are the future teachers who will teach in future using technology since future trends predict the use of technology in learning classrooms.

Social Influence

Social Influence had a significant effect on behavioral intention to use and accept formative feedback. This finding is consistent with earlier findings (Venkatesh et al., 2012). However, it must be noted that the social influence used in this study comprised of descriptive and social norms. In the original UTAUT2 model, the social influence is made of social norms and seem to work well with collectivist rather than those individualistic cultures for which South Africa is one. The descriptive norms were included because South Africa is somehow an individualistic country/culture.

The other important point is that the social influence coefficient was negative meaning that social influence and behavioral intention are inversely related. This is consistent with prior research where social influence decreases with experience (Venkatesh, et al. (2003). Perhaps in this study, the students had reached the experienced stage since all of them had been using formative feedback from high school.

There were statistically significant differences of social influence with age, gender, place and frequency of accessing the online module and time spent on assignments.

In this study, social influence had more impact on older students (Venkatesh et al., 2003). A one-way between subjects' ANOVA test indicated that there was a significant effect of social influence on age groups at the $p < .05$ level, $F(3, 171) = 2.938$, $p = .035$. Post hoc comparisons using the Games-Howell test indicated that the mean social influence score for the above 30 age group ($M = 35.75$, $SD = 2.062$) was significantly different from those for the 18 - 21 age group ($M = 29.31$, $SD = 7.964$). However, the 22–25 age group ($M = 32.01$, $SD = 7.523$), and the 26 - 29 age group ($M = 34.54$, $SD = 6.802$) did not significantly differ from the other age groups. This result was inconsistent with fact that the lower the age the more the influence of social influence (Rivis & Sheeran, 2003). However, the fact that social influence was huge for the above 30 is consistent with prior research (Morris & Venkatesh, 2000; Venkatesh, et al., 2003; Venkatesh & Morris, 2000) since older people may need help from the significant other.

From the findings, there was an indication of more social engagement with the students who spent more time on their assignments. The two robust tests for equality the, Welch and the Brown-Forsythe tests indicated statistically significant effect of social influence ($p < .05$) on time spent on assignments. Post hoc comparisons using the Tukey HSD test indicated that the mean social influence score for the students who did not take any time on their feedback assignment ($M = 23.20$, $SD = 5.541$) was significantly different to those students who took more than 120 minutes ($M = 34.78$, $SD = 3.032$). In addition, the mean social influence score for students who took between 1 to 31 minutes ($M = 28.94$, $SD = 9.001$) was significantly different to those students who took 91 minutes to 120 minutes ($M = 35.92$, $SD = 4.681$) and those students who took more than 120 minutes ($M = 34.78$, $SD = 3.032$).

There was a significant effect of social influence across categories of place and frequency of accessing the online module at the $p < .05$ level, $F(5, 169) = 2.301$, $p = 0.047$. This result suggests that social interaction would take place mostly on campus where there was unlimited connectivity rather than off-campus where there could be connectivity problems. The implication is that when lecturers are designing for online authentic activities with feedback they must take cognizance of the fact that some (poor) students may not have access to their work off-campus.

For gender, the results indicated that there was a statistically significant difference in social influence between males and females, $t(173) = -2.254$, $p = .025$. These results suggest that females ($M = 30.22$; $SD = 8.183$) had less social influence scores than males ($M = 32.84$; $SD = 6.766$). This finding is not consistent with prior research (Morris & Venkatesh, 2000; Venkatesh, et al., 2003; Venkatesh & Morris, 2000) where social influence was stronger in women than men.

Perceived Relevance

The presence of perceived relevance in the model is consistent with Escobar-Rodrguez, et al., (2014) finding that stated perceived relevance played a significant role in behavioral intention of using Facebook as a learning tool. The Welch test for equality indicated statistical significance for perceived relevance on proficiency at the end of the course, $F(3, 51.558) = 3.272$, $p = .028$, $p < .05$ probably indicating that those students who had high proficiency benefited from their perception of relevant formative feedback.

Behavioral Intention

The variance explained in the behavioral intention to use and accept formative feedback in this study is 63.6% and this is comparable to other studies in other different contexts; 72% (Escobar-Rodrguez, et al., 2014).

There was a significant effect of behavioral intention across categories of proficiency at the end of the course at the $p < .05$ level, $F(3, 171) = 3.071$, $p = .029$, $p < .05$. The result indicates that probably students who had high proficiency accepted and used feedback more readily.

Theoretical Contributions

The study adds to the existing literature that supports UTAUT2 application in diverse settings. One major theoretical contribution was to modify the UTAUT2 from the consumer technology acceptance and use context to an online formative assessment feedback in education. The UTAUT2 was applied to a "non-technological" field (formative assessment feedback) where the use of technology is secondary rather than in other studies where the UTAUT2 has been applied primarily to the use and acceptance of technology. The research contributed to identifying the factors that are important in the behavioral intention of using online formative assessment feedback.

Practical Contributions and Implications/Policy

The understanding of the factors important for the acceptance and use of formative assessment feedback can help lecturers/higher institutions in understanding the drivers of acceptance and use of formative assessment. Consequently, interventions may be put into place to enhance the use and acceptance of formative feedback. This may improve achievement in online courses, which have been characterized by high attrition rates (Greenland & Moore, 2014). For instance, on social influence, student–student engagement or lecturer-student engagement can be promoted using discussion boards, wikis, etc.

The Implication for Countries with Developing Economies

The UTAUT2 has the price value as one of its constructs and this construct was not considered because the university in question has a policy of providing internet-accessing devices to its students. This may be a problem in other universities or countries, which may not be able to afford that. Consequently, the use and acceptance of online formative feedback may be problematic. The other problem is that of internet connectivity which was nevertheless available in this study. Without access to internet connectivity, this model will not be able to work. In addition, the lecturers must be prepared to experiment with different types of authentic activities and spend more time giving feedback which may be problematic with large classes. Lack of resources may also make it difficult to employ tutors to help with feedback provision. Lastly, the students also have to be willing to get involved in these authentic activities.

CONCLUSION

In summary, the results indicate that hedonic motivation, habit, perceived relevance and social influence are important factors in the behavioral intention to use and accept formative assessment feedback in an online undergraduate module. Prior studies used social influence where it represented social norms. However, in this study social influence included both social and descriptive norms since South Africa is somehow both an individualistic and collectivist country. One more important finding is that the nature of language did not influence the use and acceptance of formative feedback. The narrative that second-language speakers of English will struggle to understand feedback must be buried since in this study it was not so. One other important factor is the level of ICT proficiency and its positive influence on perceived relevance and motivation constructs, and behavioral intention to use and accept formative feedback. Consequently, universities must continuously avail ICT upskilling programmes for the students so that increased learning outcomes can be achieved. Therefore, poor ICT proficiency can also act as barrier to the acceptance and use of formative feedback, to student motivation and perceived relevancy of feedback.

Limitations

First, the study was only limited to third-year students in the faculty of Education. Testing the model in different faculties is recommended to gauge the multi-disciplinary effect of behavioral intention on formative assessment feedback. In addition, testing the model for postgraduate students would also provide some insights since postgraduate students are more mature.

Second, the model measured behavioral intentions at a single point in time. However, behavioral intentions change over time as individuals gain experience. These changes would enable the researchers to understand the acceptance and use of formative feedback over time. Thus, the longitudinal study would test the robustness of the model for instance the effect of social influence seems to diminish with experience.

Third, another limitation of this study is the size of the sample. Although the measure for sampling adequacy (KMO) was adequate, a larger sample would have been desirable to meet the assumption requirements for regression analysis.

Fourth, the validity of the self–reported actual use of feedback could have been negatively affected by common bias, such as social desirability (Venkatesh et al., 2008). Future research should use both objective and subjective measures for method triangulation and thus improve on validity. For instance, the actual time spent on feedback was self-reported and not actually measured. Using systems logs would have given more accurate times spent on feedback.

Future Research

One of the recommendations would be to carry out the same study in different universities both inside and outside South Africa to find out about the model prediction.

The work has implication for future research in actually determining how each of the factors identified in this model influence the behavioral intention to use formative assessment. For instance, interviews can be elicited to find how each variable in the model (e.g. motivation) affects the behavioral intention to use formative assessment feedback. In other words, it is important to find out more about the antecedents of these constructs to understand behavioral intention better. Further analysis of the relationships among the constructs from UTAUT2 in the context of the acceptance and use of formative assessment feedback can be carried out in future studies by using second-generation methods of data analysis that include structural equation modeling (SEM) which does not assume the data to be normally distributed.

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Appendix

Tables Used in the Study

Table A1

Items Used in This Study

Construct	Item	Measures of elements of UTAUT2
Performance Expectancy	PE1	Using formative assessment feedback (e.g. from tutors and lecturers) improved my learning performance
	PE2	Formative assessment feedback allowed me to be more productive
	PE3	Formative assessment feedback was useful
Effort Expectancy	EE1	Using formative assessment feedback was easy for me
	EE2	Formative assessment feedback provided was clear
	EE3	I had the necessary skills to use formative assessment feedback
Social Influence	SI1	I shared some of my formative assessment feedback with my peer(s)
	SI2	My peer(s) found formative assessment useful.
	SI3	There was a culture of sharing amongst peers regarding formative assessment feedback
	SI4	My peer(s) shared some of their formative assessment feedback with me
	SI5	Most of my peers who are important to me are using formative assessment feedback
	SI6	My close friends/peers are always using formative assessment feedback
Habit	HT1	I have regularly come to use formative assessment feedback.
	HT2	I rely on formative assessment feedback to improve my learning.
	HT3	I expect formative assessment feedback in order to learn
Perceived Relevance	PR1	People who do not use formative assessment feedback are missing out on learning opportunities
	PR2	I am able to apply my learning from formative assessment feedback to other modules
	PR3	Using formative assessment feedback is essential to learning
Behavioral Intention	BI1	I will look out for formative assessment feedback in all future studies
	BI2	I intend to use formative assessment feedback regularly in all my studies.
	BI3	I will use lessons learnt from formative assessment feedback in all my future studies
Nature of Language used	L1	The language used in the assessment rubric descriptors clearly stated expected levels of achievement.
	L2	I understood the language that was used in Formative assessment feedback
	L3	The language used to provide formative assessment feedback frustrated me
Perceived Importance	PI1	I will use formative assessment feedback even when the feedback message is negative
	PI2	I will use formative assessment feedback when I understand it
	PI3	I will use formative assessment feedback when I trust its source of origin (e.g. tutor/ lecturer
	PI4	I trusted the formative assessment feedback I received in this module
	PI5	I will use formative assessment feedback when I see the importance of formative feedback in advancing my learning
	PI6	I will use formative feedback if it can be applied to future work
Hedonic Motivation	HM1	I cannot wait to apply my new learning from formative assessment feedback
	HM2	I feel encouraged by formative assessment feedback received
	HM3	When I receive negative feedback I renew my efforts to do better
Self-Efficacy	SE1	Fear of failure motivates me to use formative assessment feedback

Construct	Item	Measures of elements of UTAUT2
	SE2	I believe I will succeed when using formative assessment feedback
	SE3	Not using formative assessment feedback will result in failure
Facilitating Conditions	FC1	I had the necessary resources to use when using formative assessment feedback
	FC2	I had the knowledge necessary to use formative assessment feedback
	FC3	I feel comfortable using formative assessment feedback

Table A2

The KMO and Bartlett Test of Sphericity for All Scales

Measures	Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)	Bartlett's Test of Sphericity		
		Approx. Chi-Square	*df*	*p*
Performance Expectancy	.712	214.650	3	.000
Effort Expectancy	.688	162.233	3	.000
Social Influence	.849	574.263	15	.000
Habit	.705	175.263	3	.000
Perceived Relevance	.695	145.024	3	.000
Behavioral Intention	.751	306.666	3	.000
Nature of Language Used	.522	43.353	3	.000
Perceived Importance	.750	191.900	15	.000
Hedonic Motivation	.679	101.775	3	.000
Self-Efficacy	.628	99.362	3	.000
Facilitating Conditions	.651	96.419	3	.000

Table A3

Inter-Item Correlation

Item	Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PE1	211.33	708.154	.567	.607	.930
PE2	211.10	707.771	.605	.691	.929
PE3	211.17	703.840	.643	.677	.929
EE1	211.62	716.340	.484	.620	.930

Item	Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
EE2	211.63	704.695	.561	.601	.930
EE3	211.51	710.987	.574	.698	.930
SI1	211.81	694.165	.575	.691	.930
SI2	211.46	710.652	.548	.641	.930
SI3	211.69	699.148	.534	.719	.930
SI4	211.85	698.625	.504	.726	.931
SI5	211.46	701.974	.642	.717	.929
SI6	211.74	703.494	.613	.665	.929
HT1	211.54	694.571	.762	.741	.928
HT2	211.37	700.683	.631	.652	.929
HT3	211.23	706.100	.620	.704	.929
PR1	211.34	701.571	.625	.633	.929
PR2	211.12	706.830	.633	.645	.929
PR3	210.86	715.924	.624	.693	.930
BI1	210.89	719.470	.568	.766	.930
BI2	210.87	718.202	.592	.761	.930
BI3	210.96	715.694	.620	.743	.930
NofL1	211.03	719.987	.458	.609	.931
NofL2	211.04	722.280	.485	.637	.931
~NofL3	212.52	747.366	.001	.410	.938
PI1	211.67	735.060	.166	.320	.934
PI2	211.24	739.954	.139	.515	.934
PI3	211.16	729.710	.294	.480	.932
PI4	211.06	716.411	.560	.546	.930
PI5	211.03	739.620	.175	.449	.933
PI6	210.96	730.832	.321	.560	.932
HM1	211.10	713.261	.588	.536	.930
HM2	211.12	710.980	.645	.697	.929
HM3	210.83	719.476	.559	.565	.930
SE1	211.22	715.749	.506	.493	.930
SE2	211.11	717.787	.571	.615	.930
SE3	212.26	711.620	.404	.428	.932
FC1	211.47	713.480	.521	.491	.930
FC2	211.43	725.236	.411	.475	.931
FC3	211.05	722.566	.546	.554	.930